Parameter Estimation of Frequency Response Twin-Screw Food Extrusion Process using Genetic Algorithms

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Abstract: - Autonomic control of food extruders has attracted considerable in recent years. With limited understanding of the complex physio-chemical interactions during the food extrusion process, designing a control system for food extruder is not easy. The common approach is to determine the operating conditions and then to maintain these values as closely as possible using various control loops, if not manual control. This paper applies genetic algorithms to achieve the parameters of the twin-screw food extrusion process. The genetic algorithms are very suitable for searching discrete, noisy, multimodal and complex space. The sum of square error on magnitude and phase of the twin screw food extrusion process is minimize and receiving outstanding in shape the measured system extracted from the frequency response analysis of the food extrusion process. As recognized, exploitation of the optimization based on Genetic Algorithms gives advanced results.
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Key-Words: Parameter Estimation, Genetic Algorithms, Food, Extrusion Process, Frequency Response

1 Introduction

As Cooking food extrusion has attracted considerable attention from the food industry as it provides and efficient means for the continuous processing of a wide range of foodstuffs. Cooking extruders are already well established in the production of snack foods, baby foods, breakfast cereals and pastas. The combination of high throughput rates, energy efficiency and versatility results in the potential for improved cost effectiveness and process rationalization over traditional production methods. Despite their widespread use and economic importance, modern Process System Engineering (PSE) techniques have not been applied by the food industry to the same extents as by the chemical and petrochemical industries. This is largely due to the background of the food industry, being much more batchs and craft oriented than these other industries. In particular, cooking extruders are extremely difficult to model mechanistically due to the complex rheological properties and flow behavior of the process material, poorly understood chemical; reactions, and the almost limitless screw and die configurations possible. As a result, current cooking food extrusion knowledge consists largely of empirical correlations and operator experience [1]

With improvement in control technology, control system based intelligent search techniques have been purposed to provide enhanced control system. These methods are based on Genetic Algorithms [2-3], Neural Network [4-5] and Fuzzy system theory [6-8]

Autonomic control of food extruders has attracted considerable attention in recent years. The design of control systems requires a clear definition of the control objective and choices of control variables, identification of disturbances and manipulative variables, and choice of suitable control strategy. With limited understanding of the complex physio-chemical interactions during the food extrusion process, designing a control system for food extruders is not easy [1]

The common approach is to determine the operating conditions, such as the temperature and pressure profiles along the barrel, which give the desired product quality, and then to maintain these values as closely as possible using various control loops, if not manual control. The intention is that by controlling these secondary process variables, the product quality will also be maintained at the desired

Food extrusion is essentially a multiple-input, multiple-output (MIMO) system. The influence of disturbances and manipulative variables on different extruder output is non-linear and involves interactions and time delays. Even with MIMO control schemes, it may be impossible to control all the process outputs at the desired levels. Finally, the product quality aspect needs to be considered as the ultimate aim of the control system is to yield a consistent product quality despite disturbances and process up-sets [1]. The process variables which are available for manipulation are the feed rate F, the moisture content M, the screw speed N, and the barrel temperature profile TB(x). The process outputs include the die temperature T_{die}, the die pressure p_{die}, the product specific mechanical energy with the product bulk density ρ_B, and the product gelatinization g. Disturbances may be introduced into the process via a number of avenues, although the ones considered to be the greatest importance here are the rheological consistency index K, the tip radius of the screw R_s, which is gradually affected by mechanical wear, and the inherent moisture content of the feed material Mo.

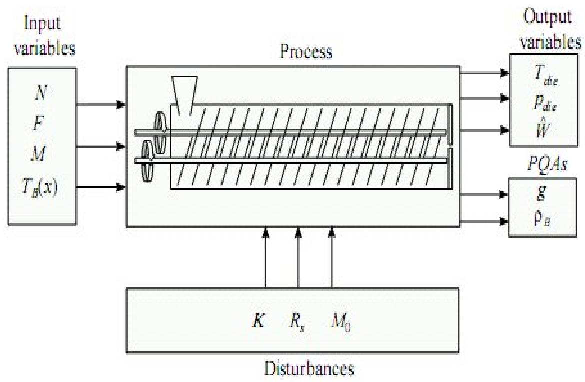

Figure 1. The food extrusion cooking process showing inputs, outputs and disturbances [9].

2 Food Extrusion Cooking Process Description

Food extrusion is a shaping operation in which a material is pressurized by some means to force it through a die. The material is generally a solid at ambient temperature, and food extrusion usually requires processing the material at a high temperature, under which the material softens or melts to facilitate flow [9] A typical extruder consists of a barrel inside which one or more helical screws rotate to prop the feed material towards a die opening at the discharge end of the extruder, as illustrated in Figure 2.

The high pressure generated during this process forces the material to exit the extruder through the die. At the same time, heat is generated due to friction and the material is exposed to high rates of shear stress.

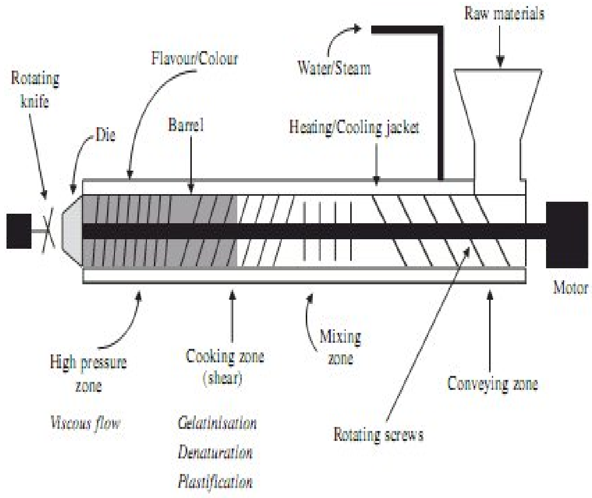

Figure 2. Schematic representation of food extrusion cooking process program [10].

This usually leads to some kind of material transformation and determines the shape, size and texture of the extrudate.

2.1 MECHANISTIC MODELLING

The steady state model presented by Kulshreshtha et al. [11] and its dynamic version, Kulshreshtha et al. [12], represent the most recent one-dimensional mechanistic modeling approach for twin-screw cooking extrusion. Both the steady state and the dynamic model are based on elemental heat and energy balances. Given the screw speed, feed rate, moisture content, feed temperature and barrel temperature profile this model calculates the temperature and pressure profiles along the barrel and the overall shaft-power required.

2.2. THE GELATINISATION MODEL

Starch gelatinisation during extrusion is a complex reaction for which the mechanisms are not fully understood. A review of the literature revealed that there have been only two different modelling approaches investigated, those suggested by Wang et al [13] and Cai and Diosady [14]. Although it is not possible to conclude which of these approaches is the more appropriate at this stage, the model suggested by Cai and Diosady has been validated over a wider range of operating conditions, and is therefore the model chosen for our implementation.

2.3. RESIDENCE TIME DISTRIBUTION (RTD)

The effect of the residence time distribution on product quality is an important consideration, as a high variance for the RTD implies a highly inconsistent degree of cooking for the product. For this reason, it is advantageous to be able to predict the RTD for a given set of operating conditions, so that the extruder can be operated in such a way as to produce a homogeneously cooked product The predicted residence time distribution of an inert tracer was compared with experimental RTD data obtained by injected sodium chloride at the feed port of the extruder [14].

2.4. EXTRUDATE EXPANSION

Extruders are often used to produce puffed products such as breakfast cereals, flat breads and snacks. For such products the expansion ratio is clearly an important quality variable. The model of Fan et al. [15] which describes the dynamics of bubble growth in starchy extrudates has been implemented in the general extruder model to provide predictions of the expansion ratio and bubble size.

2.5. RHEOLOGICAL MODELS

Dough mixes are non-Newtonian fluids, and their rheological behaviour is quite complex• The selection of a suitable theological model is crucial to the validity of the resulting extruder model, as it directly influences the flow behaviour, heat generation, and pressure development within the extruder. In a previous paper [16] two different power law model structures were compared for their accuracy at describing experimental extrusion data. However, the power law models that are typically applied often do not have a firm theoretical basis, and are therefore 1 simply correlations of a form that appear to fit experimental data over a reasonable range of conditions.

From a process systems engineering point of view, the application of a non-linear data-based modelling technique is a much more appropriate approach to this problem. Genetic Programming (GP) (e.g. McKay et al., 1996) is a novel data-based modelling technique which allows the generation of a suitable model structure and determination of the model parameters simultaneously. Hence the accuracy of model predictions is no longer dependent on a pre-assumed model structure,

2.5 ADAPTIVE INFERENTIAL EESTIMATION

Typical control variables for a cooking extrusion process are product temperature and die temperature• These variables are typically chosen because they give some indication of the state of the process and are easily measured at rates suitable for on-line process control. Ideally however, real quality measures would be the control variables, such as degree of cook, mean residence time, or product expansion ratio. Unfortunately, the feasibility of on-line measurement of these variables is limited as either the instrumentation does not exist or the analysers require long cycle times. The resulting delays would prevent early detection of the effects of load disturbances, resulting in degraded process operation

Estimators that are capable of alleviating the problem of large measurement delays and irregular sampled feedback have been previously developed [1] Since the primary controlled variable is usually related to other process outputs, the estimators make use of these secondary outputs to infer the state of the primary output each time the secondary outputs are measured. The estimators are implemented within an adaptive framework to ensure their applicability to time varying processes. The parameters of the algorithm are estimated whenever measurements of the primary output become available. As a result, estimates of the primary output are obtained at the faster rate at which the secondary outputs are measured.
To assess the feasibility of this adaptive inferential estimator (AIE) for applications to extrusion control, the AIE algorithm was used to provide estimates of the product gelatinisation fraction of an extruded starchy material, as simulated by the extruder model described earlier in this work. Product gelatinisation fraction of extruded starchy products can be determined off-line using a rapid visco- analyser. A typical analysis takes approximately 20 minutes, and thus this measurement would normally be unsuitable for process control purposes.

3. Genetic Algorithms

Genetic Algorithms (GAs) is computationally simple and independent of any assumption about search space. Moreover, they are stochastic parallel global-search algorithms based on the mechanism of natural genetics and the biological theory of evolution. GAs simultaneously evaluates many points in the parameter space, so they are more likely to converge toward a global solution. GAs is very suitable for searching discrete, noisy, multimodal and complex space.

The basic concept of the G.As where developed by Holland [17] and revised by Goldberg [18]. Goldberg shows that the GAs are computationally simple and independent of any assumption about the search space. Actually they are stochastic parallel global–search algorithms based on the mechanism of natural genetics and the biological theory of evolution. Because GAs exploit strategies of genetic information and survival of the fittest to guide their search, they need not calculate the gradient or assume that the search space is differentiable or continuous .GAs simultaneously evaluate many points in the parameter space, so they are more likely to converge toward a global solution. GAs are very suitable for searching discrete, noisy, multimodal and complex space [19], [27-29].

GAs differs from other search or optimization algorithms. First, the algorithms work with a coding of the parameter set, not the parameters themselves. Binary coding is normally used and has been suggested to be optimal in certain cases. Secondly, the algorithms search from the population of points, climbing many picks in parallel, and therefore have a reduced chance of converging to optima. Thirdly, the algorithms only require object function values to guide their search, but they have no need for derivative or other auxiliary information. Finally, the algorithms use probabilistic rather than deterministic transition rules to guide their search. Thus, these differences contributed to a genetic algorithms' robustness and resulting advantage over other more commonly used techniques [11].

When GAs is applied to solve the parallel problem, the natural parameter set of the problem needs to be coded as a finite length string (an individual). The set of all the strings is known as the population. Each string presents one possible solution to the problem. GAs begins by randomly generating an initial population of strings. Then this population evolves from generation to generation through the application of genetic operators, which imitates genetic processes occurring in nature. In every generation, all strings of the population are evacuated according to their fitness value. A simple GA is composed of three operators: reproduction, crossover, and mutation. Reproduction is based on the principle of survival of the fittest. It is a process by which strings are copied according to their fitness with greater fitness receive one or more copied, in the new population, and those with low fitness may have none. The systematic information exchange utilizing probabilistic decisions is implemented by crossover. To applying this operator, two strings are selected from the reproduced population to produce new offspring by exchanging portions of their structure. The offspring may replace weaker individuals in the population. Crossover is responsible for producing new trial solutions. Mutation is a local operator, which is applied with a very low probability of occurrence. It is the occasional random alteration of a string position to produce a new structure, which provides insurance against the permanent loss of any simple bit.

GAs efficiently exploit past information to explore new regions of the decision space with a high probability of finding improved performance, and are theoretically and empirically proven to provide robust searches in complex spaces [19], [27-29].

3.1 IDENTIFICATION PROBLEM

Generally, the method of nonlinear system, which is possible to separate into "nonlinear" and "linear" parts, is called Block-Oriented model. Absolutely, a wide range of the nonlinear system is possible to regard as separate system. In this paper we will use Hammerstein model, which the linear part is followed by the nonlinear function.

We consider discrete time linear systems so that the general structure of the Hammerstein model can be described as follows:

$$y(k) = \frac{B\left(q^{-1}\right)}{A\left(q^{-1}\right)}.\mu(k) + n(k) \tag{1}$$

Where,

$$y(k) = f(\theta, \mu(k)); \tag{2}$$

In equation (1), q^{-1} is the unit time delay, B and A are two polynomials of unknown orders and coefficients, μ, y, and n respectively represents system input, output, and stationery white noise with zero mean and finite variance, and θ is the vector parameters of the memory less nonlinear function *f*.

We implement a fixed length binary string genetic algorithms to approximate both the structure of nonlinear function and order of the polynomials, A and B.

Where,

$$A\left(q^{-1}\right) = a_0 + a_1 q^{-1} + ... + a_n q^{-n}$$
$$B\left(q^{-1}\right) = b_0 + b_1 q^{-1} + ... + b_m q^{-m} \quad (3)$$

And, nonlinear function is one of the hyperbolic function or x with unknown coefficient regarded as parameters to be estimated by the GA. This part can be both one of the functions listed in table 2 or a combination of them capable of estimating more complex function or estimate one structure more precisely. The reason for selecting abovementioned function is their resemblance to some famous hard nonlinear function, which is shown in fig. 3.

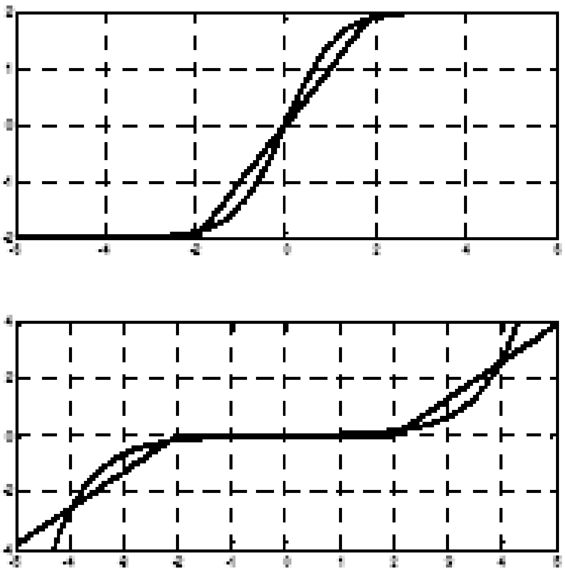

Fig. 3. Similarity between hyperbolic function and famous nonlinear function. [19].

Fig. 3 use one of the mentioned function to approximate the nonlinear function, using the combination of the basic function will help us to better approximate the nonlinear functions.

The main features of the GA are:

- *Parameters encoding*

Gene on chromosomes is composed as binary bit unit and is expressed as the binary string of limited M and the population length. Initially, this generates length with string N. The parameters are coded using binoary code. Real numbers can be coded easily with their equivalent binary representations. In order to encode the structures we made the following assumption, which has been shown in table 1.

Table 1. Basic function and their codes.

Code	Function
00	Sinh ( )
01	Cosh ( )
10	Tanh ( )
11	ax + b

- *Fitness Evaluation*

GA needs fitness for superior population formation. It can be possible with the help of the evaluation of excellence and worthlessness among strings, mainly; it is calculated from objective function. The fitness evaluation is performed every generation for each string and the results of the fitness evaluation become important information for reproduction, crossover, mutation, etc.

- *Reproduction*

Reproduction operator performs the modeling of the natural selection phenomenon, adapted string is survived, otherwise is disused. That is, the strings with high fitness increase in reproduced probability at next generation. In general, a roulette wheel selection method is used.

- *Crossover*

In an ecosystem, chromosomes occur the phenomenon of exchanging some genes. This phenomenon is designated also that the crossover. This is an important phenomenon string with the chromosomes of finite numbers obtain genetic variation. In general, the probability raising crossover between two strings is from 0.6 to 0.95. In search course, the genetic search method has merits because it can obtain the global performance superior to parents through local action among chromosomes. Crossover carries out the core role in GA.

- *Mutation*

Mutation is phenomenon making new traits by the sudden form change of genes. Mutation is also an important factor as crossover. In general, GA are possible to the global shift as well as the local search by mutation. The mutation probability should be selected from 0.001 to 0.01 because rises regardless of adaptation of environment mutation randomly. If the mutation probability is very high, it can lose important traits. Therefore, it must be selected properly. Finally, the flowchart of GAs is shown in Fig. 4 [2-3][11].

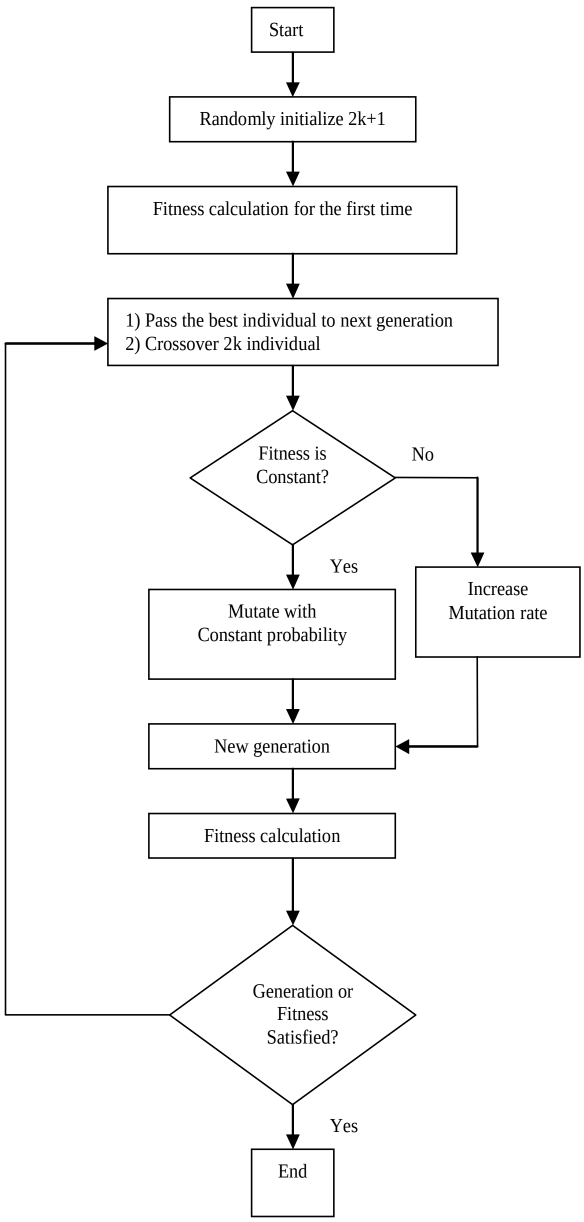

Fig. 4. Flowchart of Genetic Algorithms [10].

4. Mathematical models

Wang et al [20] presented a three stage approach to system identification and demonstrates that each stage is both simple to apply and transparent in its results. The three stages are:

Data acquisition using relay feedback: An automated technique for experimental data acquisition based on the relay feedback approach of Astrom and Hag-glund [21], but with modified periodic oscillations.
Step response using frequency-sampling filters: Identification of the system step response from the experi-mental data using the frequency-sampling filter (FSF) approach of Wang and Cluett [22].
Continuous-time transfer-function identification: Identification of a (continuous time) transfer function from the identified step response.

Each stage is automated, yet the output of each stage is readily understandable and can be examined by the process engineer before proceeding to the next stage.
Thus the first stage yields data corresponding to square waves at the correct frequency to yield useful information and the process engineer can adjust input and output amplitudes according to his knowledge of process behavior. The second stage gives a step response which is much ‘cleaner’ (in terms of noise and disturbance) than that obtained by a simple step response experiment and therefore can be matched to the experience and intuition of the engineer. The third stage yields a transfer function approximation to the step; the order of the transfer function can be chosen by the process engineer to trade off accuracy against complexity whilst yielding numerical values for steady-state gains, time constants, natural frequencies and damping.
One of the essential ideas behind the proposed approach is associated with the idea of data compression in which the process experimental data using binary input signals are compressed into step responses. During this compression process well-established system identification tools and methods in discrete systems can be applied to obtain high quality step response models.
High quality step response models with little noise will lead to the estimation of continuous time transfer function models with high accuracy (as demonstrated in this paper). In addition, the number of data points contained in a step response model is far less than the number of data points in a set of

process experimental data using a binary input signal, which is inevitably advantageous in numerical computation of a continuous time transfer function model. It is worthwhile to point out that use of state-variable filters in the estimation of a continuous time transfer function model is essential for overcoming the well-known lack of excitation problem when a step input signal is used.

There was an attempt to identify a continuous time transfer function model of food extruder directly from input and output data using state-variable filter approach. However, because of the high noise level existed in the measurement of food extruder, it was numerically sensitive for the estimation of the pole locations in the continuous time model, as well as for the choice of state variable filters, even though a large number of experimental data were used. In contrast, in the proposed approach as the continuous time system estimation is set on the second stage of the estimation problem, it is anticipated that higher quality continuous time models will be obtained when there is little noise in the step response data.

4.1. DATA ACQUISITION USING RELAY FEEDBACK

A simple relay is a nonlinear element that switches between the levels -a and +a based on the error signal *e* and generates a square wave input signal u to the process. In the extruder case, the process outputs are corrupted with noise, hysteresis is added to the relay to reduce the effect of the noise (see Fig. 5). Adding hysteresis to the relay produces a dead-zone to prevent the relay signal from switching due to the noise. It is well known that if the width of the hysteresis ε equals zero, then the oscillation frequency corresponds to the crossover frequency of the process under the feedback control. An integrator in series to the relay element generates a stable oscillation with the dominant frequency corresponding to -90^{o} on the Nyquist plot [21].

A standard relay experiment produces in most cases a limit cycle dominated by a single frequency. However, this information is not sufficient for the estimation of a continuous time transfer function model. The strategy we adopt in the identification experiment design was introduced [23]and applied by Wang and Gawthrop [24] to simulation studies of continuous time system identification, in which we make use of multiple relay experiments to generate frequency response information at several frequencies. The proposed apparatus combines in parallel a relay element with an integrator in series with a relay element. Fig. 5 provides a block diagram of this apparatus. The experiment is performed by alternatively switching the error signal between the relay path and the integrator-relay path. The design of the experiment then reduces to the selection of this switching sequence. The proposed relay experiment on its own provides some interesting ideas about how to design input signals for continuous time identification. One of the main benefits of the apparatus is that the design of an identification experiment suitable for obtaining a mathematical model has now been automated. In addition, choice of sampling rate can be set to near continuous measurement.

Wang et al [20] combined stages approach to system identification in a novel way and verified the approach in an industrial application context.

A multi-frequency relay feedback control system [5] was implemented on the food extruder to ensure safe operation of the process when doing identification experiment and to obtain experimental data that have relevant frequency content for dynamic modeling. Continuous-time transfer function models were estimated using the state-variable filter approach presented in Wang

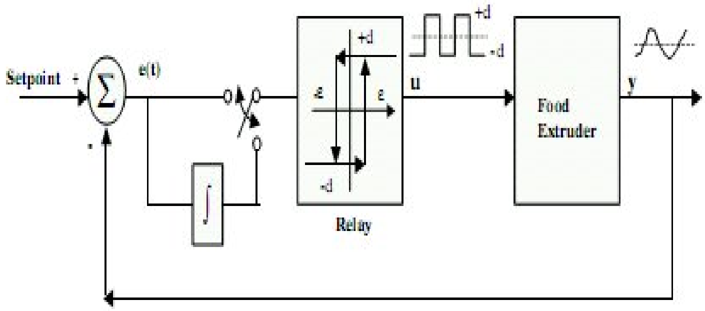

Fig 5. Data acquisition: multi-frequency relay feedback system [20].

and Gawthrop [9][26-27]. More specifically, suppose that μ_1, μ_2, y_1 and y_2 represent screw speed, liquid pump speed, SME and motor torque, respectively.

Then the continuous-time model for the food extruder is

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} G_{11} & G_{12} \\ G_{21} & G_{22} \end{bmatrix} \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}, \quad (4)$$

$$G_{11} = \frac{0.21048s + 0.00245}{s^2 + 0.302902s^2 + 0.066775s + 0.002186},$$
$$G_{12} = \frac{-0.001313s^2 + 0.000548s - 0.000052}{s^2 + 0.210391s^3 + 0.105228s^2 + 0.00777s + 0.000854},$$
$$G_{21} = \frac{0.000976s - 0.000226}{s^2 + 0.422036s^2 + 0.091833s + 0.003434},$$
$$G_{22} = \frac{-0.000017}{s^2 + 0.060324s + 0.006836}.$$

The continuous-time transfer function models have been validated using four sets of experimental data which are independent from the data sets used for estimating the models. For the equation it could be in the normal form as the following:

$$G(s) = \frac{b_m s^m + ... + b_1 s + b_0}{a_n s^n + ... + a_1 s + a_0} \quad (5)$$

Or

$$G(s) = \frac{k(s+z_1)(s+z_2)...(s+z_m)}{(s+p_1)(s+p_2)...(s+p_n)} \quad (6)$$

The objective function is the sum of square error (SSE) as the following [3]:

$$SSE = \sum_{i=1}^{N} \left(y_{measured} - y_{simulated} \right)^2 \quad (7)$$

$y_{measured}$: the measured magnitude and phase on frequency response characteristics

$y_{simulated}$: the simulated magnitude and phase on frequency response characteristics

5. Simulation Results

The parameters describe by following are setting for the Genetic Algorithms used in this paper.

GA:
Number of population = 50
Crossover = 4
Mutation = 8

Variable : G_{11} Range

b_0:[0, 0.01225]; b_1:[0,1.0525];
a_0: [0, 0.01095]; a_1:[0, 0.33385];
a_2:[0, 1.51450]; a_3:[0,5]

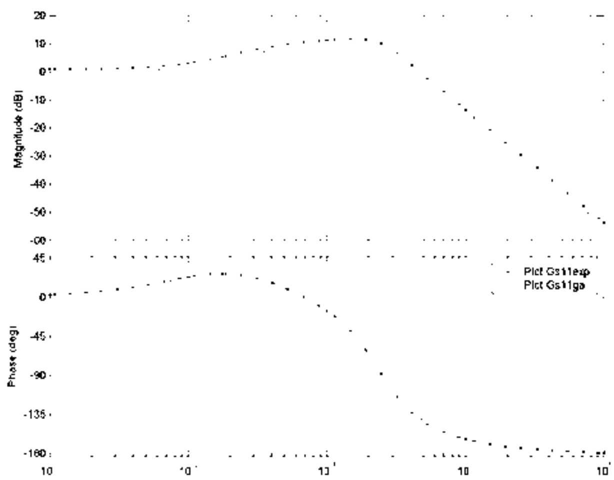

Fig. 6. Frequency response characteristics of the system and the Genetic Algorithms with by SSE for screw speed input and SME output.

Table 2. Comparison among obtained parameters for screw speed input and SME output.

Parameters Methods	Poles	Zeros
G_{11}	-0.13212+0.19774i -0.13212-0.19774i -0.03864	-0.01164
GA	-0.13266+0.19536i -0.13266-0.19536i -0.04054	-0.01220

It could be seen that the best control performance was obtained using SSE for screw speed input and SME output. Moreover the obtained parameters shown in Table 2 are very closed when compared between system and Genetic Algorithms.

Vriable G_{12} Range
b_0 :[-0.00025, 0]; b_1 :[0, 0.00275];
a_0 : [0, 0.00425] a_1:[0, 0.03885] ;
a2:[0, 0.52615]; a_3: [0, 1.051955];
a_4:[0,5]

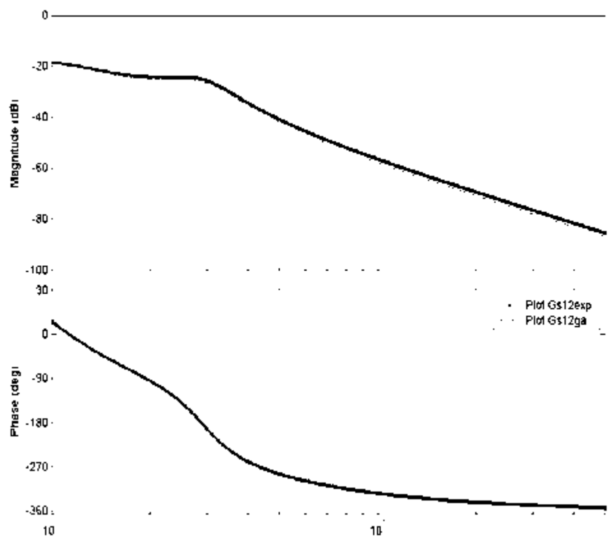

Fig. 7. Frequency response characteristics of the system and the Genetic Algorithms with by SSE for liquid pump speed input and SME output.

Table 3. Comparison among obtained parameters for liquid pump speed input and SME output.

Parameters Methods	Poles	Zeros
G_{12}	-0.06746+0.28363i -0.06746-0.28363i -0.03773+0.09286i -0.03773-0.09286i	0.27148 0.14587
GA	-0.06757+0.28620i -0.06757-0.28620i -0.03201+0.09658i -0.03201-0.09658i	0.26098 0.16263

It could be seen that the best control performance was obtained using SSE for liquid pump speed input and SME output. Moreover the obtained parameters shown in Table 3 are very closed when compared between system and Genetic Algorithms.

Variable G_{21} Range
b_0:[-0.00115, 0]; b_1 :[0, 0.00490];
a_0: [0, 0.01715]; a_1 : [0, 0459165];
a_2:[0, 2.11015]; a_3:[0,5]

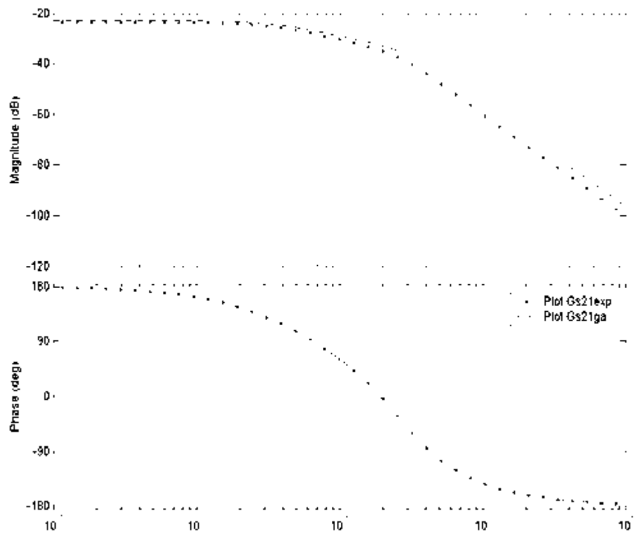

Fig. 8. Frequency response characteristics of the system and the Genetic Algorithms with by SSE for screw speed input and motor torque output.

Table 4. Comparison among obtained parameters for screw speed input and motor torque output.

Parameters Methods	Poles	Zeros
G_{21}	-0.18797+0.19791i -0.18797-0.19791i -0.04609	0.21012
GA	-0.20005+0.21012i -0.20005-0.21012i -0.49102	0.19465

It could be seen that the best control performance was obtained using SSE for screw speed input and motor torque output. Moreover the obtained parameters shown in Table 4 are very closed when compared between system and Genetic Algorithms.

Variable G_{22} Range
b_0 : [-0.000085, 0]; b_1 : [0, 0];
a_0: [0, 0.03420]; a_1: [0, 30160];
a_2:[0,5]

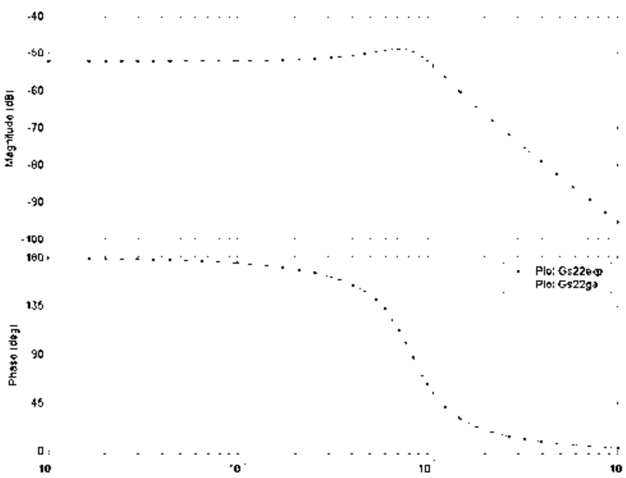

Fig. 9. Frequency response characteristics of the system and the Genetic Algorithms with by SSE for liquid pump input and motor torque output.

Table 5. Comparison among obtained parameters for liquid pump input and motor torque output.

Parameters Methods	Poles	Zeros
G_{22}	-0.03016+0.07698i -0.03016-0.07698i	0
GA	-0.03014+0.07699i -0.03014-0.07699i	0

It could be seen that the best control performance was obtained using SSE for liquid pump input and motor torque output. Moreover the obtained parameters shown in Table 5 are very closed when compared between system and Genetic Algorithms.

For all simulation results, the results simulated by using the parameters obtained from the Genetic Algorithms are reasonable when compared with system data.

6. Conclusion

This paper illustrates the genetic algorithms to estimate parameters of the twin screw food extrusion process. The comparison between obtained parameters from system data and genetic algorithms are investigated. GAs efficiently exploit past information to explore new regions of the decision space with a high probability of finding improved performance. Finally, this result could be applied for further model predictive control system (MPC) in steady-state operating conditions, regulatory control, and reference following control.

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